QUANTIFYING AND REDUCING UNCERTAINTY IN MICROWAVE VEGETATION OPTICAL DEPTH AND SOIL MOISTURE RETRIEVALS

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ABSTRACT

Soil moisture and vegetation optical depth (VOD; related to vegetation water content) retrieved from SMAP and SMOS satellites are widely used for a range of hydrosphere and biosphere applications. However, while soil moisture has been globally well-validated, VOD validation has been sparse. Furthermore, simultaneous retrieval of these parameters results in uncertainties both individually in soil moisture and VOD retrievals as well as in compensation between the parameters. Here, we show global locations where soil moisture and VOD retrievals will have lower uncertainty, based on complementary brightness temperature information content and signal-to-noise ratio metrics. In these same locations, we show that error propagates more into VOD. However, using VOD regularization algorithms, this error is greatly reduced, especially at sub-weekly timescales where algorithmic error can be most apparent. Despite these regularization approaches that reduce errors, there are yet vast differences in available global regularized retrievals originating from different algorithmic choices.

Index Terms— Passive microwave radiometry, SMAP, vegetation optical depth, soil moisture, uncertainty

1. INTRODUCTION

Soil moisture and vegetation optical depth (VOD) obtained from passive microwave remote sensing missions are increasingly being used as an observational constraint on land surface hydrology and ecosystem science. However, while soil moisture has been validated across established global in-situ sites, a similar scale VOD validation has yet to be attempted. This is despite an increased use of VOD in ecosystem sciences as well as evidence that VOD strongly influences soil moisture retrievals [1]. With only sparse VOD validations being attempted [2], it is necessary to establish holistic metrics that detect and quantify error propagation of satellite measurement errors into soil moisture and VOD algorithmic retrieval error. Additionally, approaches that reduce error in VOD have been developed under a common theme of regularization, or imposing a priori information about VOD in the algorithm [3]. However, the retrieval error reduction from these regularization approaches has only recently began to be quantified [1], [4] and differences between regularization approaches remain to be investigated.

Here, our objectives are to (i) establish holistic metrics that evaluate how confidently soil moisture and VOD can be simultaneously retrieved from a pair of brightness temperature measurements as well as (ii) estimate and evaluate retrieval uncertainty reduction using regularization.

2. UNCERTAINTY METRICS

We evaluate two metrics that inform how well passive microwave retrieval algorithms can simultaneously retrieve soil moisture and VOD using the tau-omega model. We use SMAP L1C brightness temperature (TB) at 9km resolution that produce official SMAP soil moisture products.

First, the degrees of information (DOI) is computed:

$$DOI = N - c_n \quad (1)$$

where N is the number of measurements and c_n is their total normalized correlation [5]. When there is more shared information between the measurements, c_n increases, indicating less independent information to retrieve unknown parameters. When considering polarized TB measurement pairs, the DOI estimates an upper bound on how many unknown parameters can be retrieved with these two measurements. Values below two indicate that, due to correlated TB measurement pairs, both soil moisture and VOD cannot be simultaneously retrieved without estimation instabilities that amplify retrieval error.

Fig. 1A shows the global spatial pattern of DOI where most locations are well below 2 and near 1.5. The values curiously approach 2 in forested regions, suggesting less retrieval uncertainty. This is despite it being well known that soil moisture retrieval errors are greatest under dense vegetation because of a reduced detection of soil emission as well as neglect of multiple scattering in the radiative transfer equation. As such, DOI's intended use breaks down in these locations. This issue arises because DOI can undesirably approach 2 in cases where both measurements are dominated by random, independent noise [6]. This can occur in forests

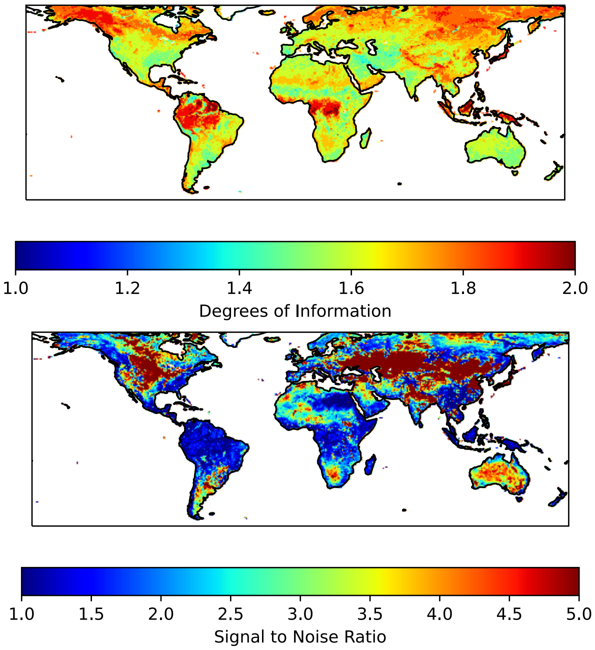

Figure 1. (A) Degrees of information. (B) Signal to noise ratio. Based on SMAP L1C brightness temperature measurements.

where the TB_H and TB_V difference is dominated by random noise, instead of the desired, natural polarization differences that delineate soil from vegetation signals. Therefore, a separate metric is required that detects this desired TB_H and TB_V difference.

Namely, the signal-to-noise ratio (SNR) achieves this aim complementary to DOI as computed by:

$$SNR = \frac{\sigma^2(L)}{\left(NEDT_V^2 + NEDT_H^2\right)} \qquad (2)$$

Here, $\sigma(L)$ is the standard deviation of L, the distance of a given TB_H and TB_V measurement pair from their 1:1 line. As such, L is a measure of signal in measuring the difference between TB_H and TB_V. TB polarizations ultimately need to differ to a large enough degree to confidently partition soil and vegetation signals. The Noise Equivalent Delta Temperature (NEDT) represents measurement error in the SMAP L1C TBs which are approximately 1K.

Most low-to-moderately vegetated regions of the globe have SNR well above 2 indicating a high potential to confidently partition soil and vegetation signals from the available observations (Fig 1B). It also shows SNR approaching 1 in forested regions where DOI is high. This indicates that TB_H and TB_V differences are dominated by random noise rather than physically meaningful differences needed to disentangle soil and vegetation signals. Nevertheless, SNR alone is misleading because while it is high in semi-arid locations, DOI indicates that more information beyond the TB_H and TB_V pair at a location is needed to confidently retrieve soil moisture and VOD.

Ultimately, these complementary metrics reveal that there are no instances where both conditions are met with DOI being near 2 and SNR being above 2 (Fig. 1). Retrievals of soil moisture and VOD will thus have amplified error due to retrieval instability if using a simultaneous retrieval approach (i.e., DCA, LPRM).

However, increasing the DOI through regularization (as in the MT-DCA; see Section 3) would allow for higher confidence in retrieval stability, especially for VOD across light-to-medium vegetated regions across the globe (Fig. 2).

To inform the regularization approaches needed as suggested in Figs. 1 and 2, it is key to determine how the amplified error in a simultaneous retrieval approach propagates into soil moisture and VOD. We use the difference of the individual soil moisture (SM) and VOD SNR:

$$SNR\ Difference = \frac{\sigma(SM)_{Signal}}{\sigma(SM)_{Error}} - \frac{\sigma(VOD)_{Signal}}{\sigma(VOD)_{Error}} \qquad (3)$$

where values greater than zero indicate that error is propagating more into VOD than soil moisture. The SM and VOD errors are determined numerically by computing the error covariance matrix of the cost function at each pair of soil moisture and VOD as shown in [4]. The SM and VOD signals are estimated by determining the sub-seasonal standard deviation of retrieved SM and VOD.

Based on Eq. 3, error tends to propagate more into VOD than soil moisture across the globe (Fig. 3). It does so to such a degree that the VOD signal would need to be a factor

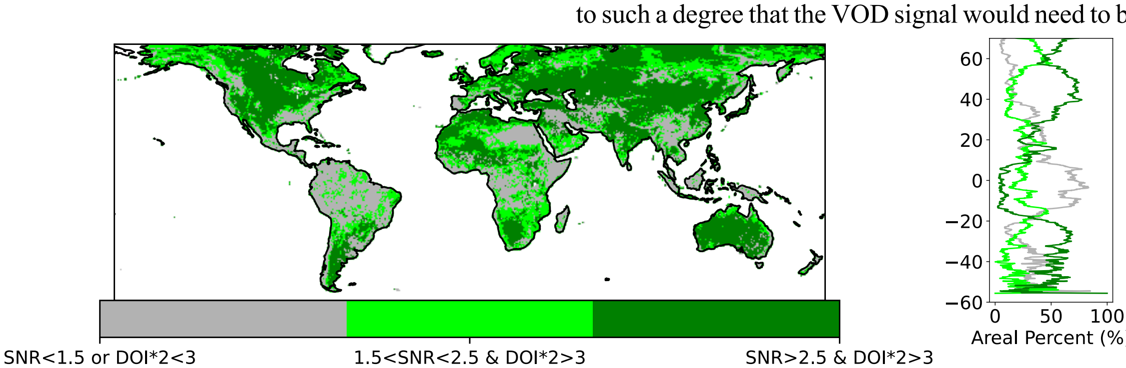

Figure 2. Locations where joint soil moisture and VOD retrievals have low uncertainty with regularization (dark green: higher confidence; light green: medium confidence). Right: Areal percent of conditions met with latitude.

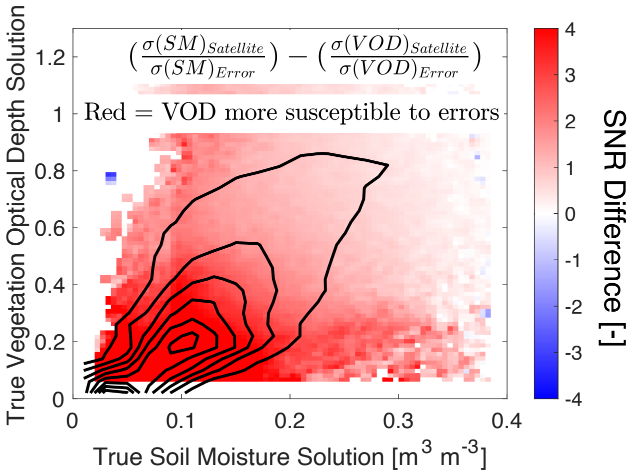

Fig. 3. Degree of error propagation into VOD relative to soil moisture. Estimate of the SNR difference in Eq. 3 using SMAP satellite retrievals where each global 36 km land pixel includes a value plotted on this joint density. Black contours show the joint density of SMAP time-mean values of soil moisture and VOD across the globe. Reproduced with permission from ref [4].

of two to four times higher for error to instead propagate into soil moisture. This may occur because of the tendency for error variability to move along the VOD axis in the cost function space [3].

3. RETRIEVAL USING REGULARIZATION

Ultimately, given a tendency for error to propagate into VOD and that DOI is not high enough to robustly retrieve both soil moisture and VOD with two TB measurements, an error mitigation approach is accordingly needed in the retrieval algorithm. A common approach is using regularization, or solving an underdetermined problem by imposing a priori information about SM and/or VOD in the retrieval algorithm. Given that error propagates more into VOD (Fig. 3) and that it is a viable assumption that VOD variations are slower than soil moisture in time with the influence of dry biomass changes [7], passive microwave retrieval algorithms stabilize retrievals by making assumptions that slow VOD in time. Namely, the multi-temporal dual channel algorithm (MT-DCA) slows VOD using a discrete time-window approach imposing constrains on its rate of change between overpasses [3]. The SMAP modified dual channel algorithm (referred to here as MDCA, but officially named DCA) now similarly uses a Tikhonov regularization approach that slows VOD variations by imposing constraints on VOD deviations from MODIS NDVI climatology.

We simulate "true" (or perfectly known) soil moisture and VOD time series as in ref. [4] that resemble retrieved SM and VOD. These values were input into the tau-omega model to generate true, TB time series. Random, normally distributed TB error on the order of that observed

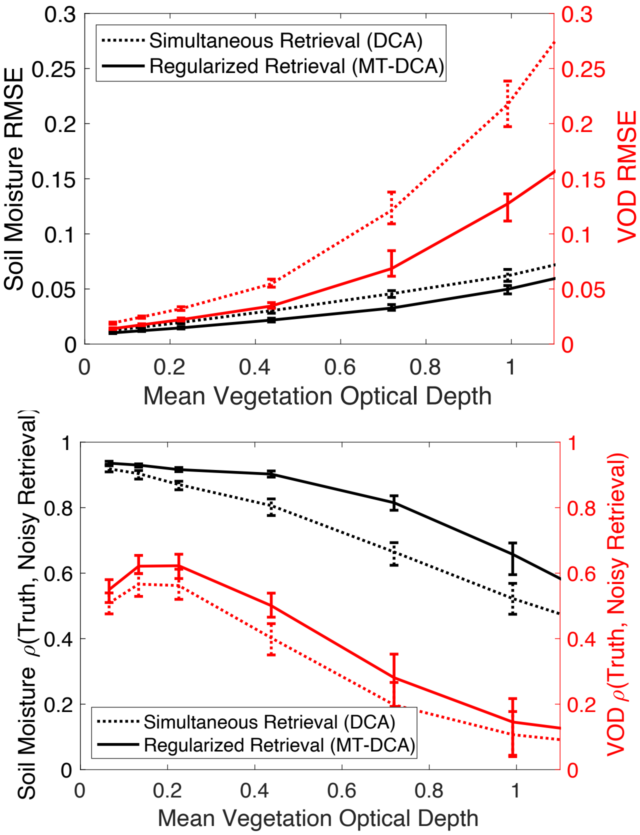

Fig. 4. Regularization reduces both soil moisture and VOD errors, especially for their high frequency components (<10 day periods). (A) Root mean square error of soil moisture and VOD. (B) Correlation between simulated noisy time series and truth for soil moisture and VOD for their high frequency components (<10 day periods). Error bars show 95% confidence interval. Computed given a 1.1K TB error standard deviation and average soil moisture of 0.2 m^3 m^{-3}. Reproduced with permission from ref [4].

(i.e., N(0, 1.1K)) was added. Both MT-DCA (regularized) and traditional simultaneous DCA (non-regularized) were used to retrieve SM and VOD from these noisy simulated TB time series to (a) quantify the propagation of error in comparing to the "true," simulated SM and VOD time series as well as (b) determine the error reduction caused by regularization. Both algorithms used the same input parameters to isolate only the effect of regularization.

Soil moisture and VOD errors increase with mean VOD (Fig. 4A), as expected from uncertainty metrics in Fig. 1. However, regularization reduces these errors, especially more in VOD as expected from Fig. 3. VOD RMSE is reduced by 36% on average and soil moisture RMSE reduced by 22% on average. Regularization slows VOD variations in time, which one may expect would reduce VOD correspondence to truth at sub-weekly timescales. However, we show here that it increases VOD's correlation with the truth at these short timescales, as well as for soil moisture

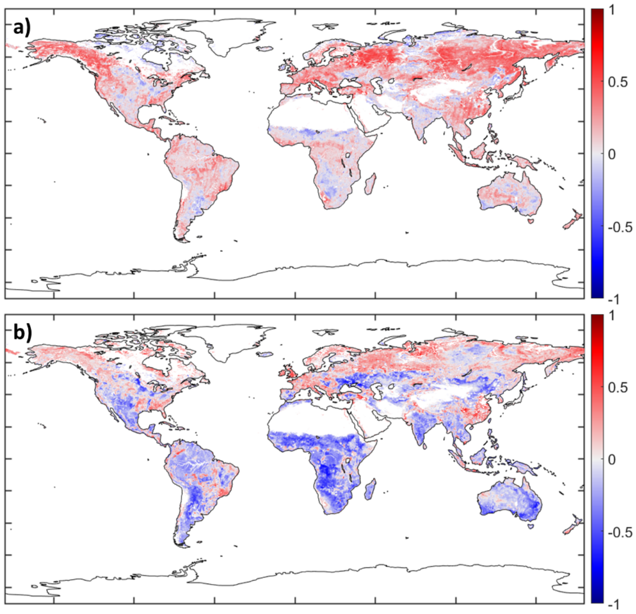

Figure 5. Correlation between soil moisture and VOD for their high frequency components (<10-day periods) using regularization algorithms: (A) SMAP MT-DCA. (B) SMAP MDCA.

(Fig. 4B). This indicates the benefit of regularization in reducing error within the algorithm and mitigating the underdetermined problem posed in Fig. 1. As such, SM and VOD variations produced from regularization have an improved capability in understanding global, sub-weekly soil-plant moisture dynamics [8]. We found that these results similarly hold using a similar Sobolev-norm regularization approach. However, such simulations have yet to be performed on the SMAP MDCA's Tikhonov regularization. While we expect similar results, the error reduction will additionally be function of the input VOD a priori variations.

We finally highlight that while regularization is known to confer error reduction benefits to both SM and VOD, the retrieved dynamics can differ when using different regularization assumptions. Figure 5 shows that soil moisture-VOD coupling at sub-weekly timescales can be vastly different across the globe. The MT-DCA uses a naïve retrieval approach that assumes slower VOD dynamics, but does not explicitly impose their functional form. Conversely, the MDCA Tikhonov approach inputs an a priori VOD time series. It is important to ultimately rectify whether the differences in Fig. 5 arise from differing constraints in altering the degree of regularization or from the functional form of the input a priori VOD in the MDCA. Ultimately, the appearance of negative SM-VOD correlations in global semi-arid regions in both products suggests that error is being mitigated and natural dynamics are emerging. Positive correlations instead may indicate the presence of erroneous compensation within the algorithm as appears in traditional simultaneous DCA retrievals [4].

4. CONCLUSION

Here, we find that the signal to noise ratio and degrees of information metrics show that low to moderately vegetated areas of the globe are most robust to retrieval error. However, some degree of regularization is needed to stabilize retrievals, especially with error propagating more into VOD than soil moisture. Ultimately, regularization reduces both soil moisture and VOD errors, especially at sub-weekly timescales. Nevertheless, available soil moisture and VOD products that implement regularization show differences in retrievals, the origins of which require investigation.

5. REFERENCES

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